International Journal of Innovative Computing, Information and Control
Volume **9**, Number **10**, October **2013**
ICIC International ©2013 ISSN 1349-4198
pp. 4101–4111

AN INNOVATIVE DISTRIBUTION PROPORTION APPROACH FOR THE MEDICINES IN HSCM BASED ON TOTAL SYSTEM COST AND PATIENT SAFETY

Hung-Chang Liao[1,2,*] and Yan-Kwang Chen[3]

[1]Department of Health Services Administration
Chung Shan Medical University
No. 110, Sec. 1, Jian-Koa N. Road, Taichung 40201, Taiwan
*Corresponding author: hcliao@csmu.edu.tw

[2]Department of Medical Management
Chung Shan Medical University Hospital
No. 110, Sec. 1, Jian-Koa N. Road, Taichung 40201, Taiwan

[3]Department of Distribution Management
National Taichung University of Science and Technology
No. 129, Sec. 3, Sanmin Road, Taichung 40401, Taiwan

Received September 2012; revised January 2013

Abstract. *This paper proposes an innovative distribution proportion approach for medicines for hospitals that have combined their hospital supply chain management (HSCM) for the centralized purchasing of medicines. This approach is fit for hospitals who do not engage in open information sharing related to internal costs. Neural networks (NNs) and genetic algorithms (GAs) are the core technologies of this distribution approach wherein each hospital's total cost and patient safety level were considered. This paper looks at possible computational results of these technologies, and discusses adjustment strategies for different distribution proportions of medicines to different hospitals.*
Keywords: Hospital supply chain management (HSCM), Patient safety, Genetic algorithm (GA), Neural network (NN)

1. **Introduction.** Supply chain management is a tremendous challenge to managers. Traditionally, a manager focuses only on internal material flow to decrease total cost and improve profitability. However, managers needs to integrate material flow with the decisions and activities of external business partners. Zijm and Timmer [1] developed a coordination mechanism for inventory control of the supply chain in both three-echelon serial systems and distribution systems that had decentralized control to minimize inventory costs. Chen and Tu [2] developed an agent-based manufacturing control and coordination system in order to control dynamic production flows and to improve mass customization manufacturing processes. Chu and Leon [3] developed a scalable methodology for supply chain inventory coordination with multi-echelon dynamic lot-sizing problems. Pan et al. [4] developed an optimal reorder decision-making strategy to increase coordination in an apparel supply chain flow in a dynamic environment. Sajadieh, Jokar and Modarres [5] developed a coordinated vendor-buyer model in two-stage supply chains to minimize the expected total costs of both buyers and sellers.

The supply chain system is a dynamic behavior not the static control of activities. Simulation is an effective tool in evaluating the control mechanisms of dynamic behaviors of supply chains. Fleisch and Tellkamp [6] simulated the relationship between inventory inaccuracy and performance in a retail supply chain and proved that the decrease of inventory inaccuracy can reduce costs in the supply chain. Zhang and Zhang [7] presented a simulation of information sharing on demand in a supply chain that would help firms make better decisions on business model designing and inter-organizational collaboration in supply chains. Longo and Mirabelli [8] used an advanced supply chain management tool based on modeling and simulation to analyze the effects of inventory control policies on three different supply chain performance measures. Chen and Chen [9] developed a modular approach to help with supply chain integration and the exchange of information to increase business efficiency. Kofjac, Kljajic and Rejec [10] developed an anticipative concept to cope with the instability of business environments and to minimize total inventory costs. Kitagawa et al. [11] created a supply chain simulation tool to evaluate and quantify supply chain models in order to avoid subjective decision making.

Research concerning the coordination of supply chains tends to focus on manufacturing and retail sectors; there is less research on hospital supply chain management (HSCM). Donk [12] proposed a practical approach to evaluate and plan improvements in a supply chain relationship between a large hospital and its supplier of medical and non-medical gasses. Nicholson, Vakharia and Erenguc [13] researched the outsourcing of inventory management decisions for inventory cost savings in a healthcare setting. Lapierre and Ruiz [14] used a Tabu search to improve hospital logistics and better coordinate purchasing and procurement in a case in Montreal, Canada. Liao [15] studied how to decide on purchasing quantity while considering patient safety and minimizing total costs in an HSCM.

In Taiwan, patient safety is an important issue in hospitals as they strive to improve service quality and patient satisfaction [16,17]. Based on the studies mentioned above, this paper discusses the development of a dynamic simulation model of a Taiwanese HSCM based on a strategic alliance of three regional hospitals. The HSCM purchases medicines in order to minimize total system costs and to obtain adequate patient safety levels based on each hospital's proportion of distributed medicines. The research motivation focuses on the distribution proportion of medicines for each hospital when these hospitals' open information sharing of internal costs is almost impossible. A mixture experiment, a genetic algorithm (GA), and a neural network (NN) were used to compute these distribution proportions. Also, a practical problem for how to compute the distribution proportions for each hospital was explored and compared with the innovative distribution proportion approach.

The next section of this paper introduces the GA and NN. Section 3 states the HSCM problem needing to be solved and analyzed based on the result of the computations. Section 4 shows the sensitivity analysis for the optimal distribution proportion of medicines for each hospital. Section 5 presents a summary of the findings and contributions.

2. **NN and GA.**

NN Procedure. An NN is a soft computing algorithm that has been used as a research tool in many different fields, including medical diagnoses, signal processing, pattern recognition, and financial analysis [18]. An NN is designed to emulate a human neurological system, which is constructed with parallel processing units called nodes. The nodes have a structural interconnection and knowledge is produced through the relationship between input and output nodes, which store the inner product of synaptic weights. The transfer function is used for the weighted sum of the previous input neuronal layers with the exception of the first layer. Different transfer functions used in the NN result in the wide-ranging application of NNs. NNs produce a black-box mathematical model, which is a form of network structure. Research [19-21] shows NNs are effective for addressing complex nonlinear problems if network architecture and parameters are adequately selected.

GA Procedure. A GA is a soft computing algorithm that is an optimization methodology for solving nonlinear programming. The concept of GAs developed from Darwinian natural selection and genetics [22]. The search techniques for GAs are different from traditional search techniques, which are conducted using a point-to-point search route in the feasible solution space. For GAs, the Darwinian principle of "survival of the fittest" is applied, and an optimal solution is found by using a set of candidate solution, population, conducting a series of iterative computations, and using stochastic nature characteristics to treat large search spaces with complex problems randomly but efficiently [23]. GAs generate a chromosome, which represents a series of alternate solutions, and quickly produce a successful solution without testing all possible solutions. Three main operators – selection, crossover, and mutation – are used to improve the fitness of a population of guesses when the optimal solution is converged [22].

3. **The HSCM Distribution Problem.** In this paper, the HSCM of an alliance between three regional hospitals in central Taiwan is reviewed. The alliance was formed to create a centralized purchasing center (CPC). The hospitals chose to centralize purchasing because most medicines have patent right limitations and drug maker monopolies that result in high prices. Through a CPC, the large ordering quantities result in a discount advantage for each hospital, resulting in a competitive advantage by reducing total costs in each hospital. To compute the purchasing quantity, it is necessary to have the total system cost of the supply chain system [24-28]. However, in the strategic alliance under discussion, obtaining each hospital's internal costs to calculate the total system cost was difficult. In fact, open information sharing of internal costs was almost impossible.

This alliance also experienced a distribution problem in the centralized purchasing system [29]. Dispatching appropriate quantities from the total to each hospital resulted in a trade-off effect between service level and total cost in each hospital. Based on the material flow of HSCM systems [30-33], adequate supplies of medicines can be an important factor in analyzing patient safety. Service level can thus be a feasible index to measure shortages of medicine, and by extension, patient safety level. Therefore, in this paper, service level is used as the index of patient safety level [15]. The trade-off effect between total cost and service level in each hospital means that different quantities dispatched to each hospital can affect service level and total cost in each hospital. By obtaining larger quantities, service levels will improve because of a decrease in inventory shortage probability; however, the inventory will increase total costs.

To solve this HSCM problem, this paper considers a distribution proportion approach that will rapidly be able to suggest quantities necessary for dispatch to each hospital. This innovative distribution proportion approach can simultaneously overcome the difficulty of not having open sharing of internal costs and the distribution problem of obtaining efficient quantities. One medicine's centralized purchasing and distribution is used to illustrate the innovative distribution proportion approach (Step 1 to Step 4).

Step 1: Obtain the interval estimation of total cost and service level at each of the three hospitals using past histories of obtaining quantities.

Because open information sharing of internal costs between hospitals was almost impossible, the CPC asked each hospital's accounting department to submit their archives of obtaining quantities, including total cost and service level. For example, if the medicine's ordering quantities were 10,000-11,000 tablets, the total cost to the hospital would be between \$35,000 and \$38,000 (all dollar amounts listed are in American dollars) and the service level would be between 0.82 and 0.85. Table 1 shows the interval estimation of distribution proportion of the obtaining quantities, interval estimation of total cost, and interval estimation of service level for 50,000 tablets. Notably, the CPC decision maker must estimate the least quantities of the medicine for each hospital, and establish a range of interval estimation of distribution proportion that is not too long. The reason is that after establishing the mathematical model, the more precise optimal distribution proportion will be found more easily.

Step 2: Use mixture of experiment to obtain samples of distribution proportion of the obtaining quantities.

The distinguishing feature of the distribution proportion is that the independent factor represents the proportion amount of the mixture [34]. The proportions of mixtures are non-negative. If q represents the number of ingredients in the system under study and if we represent the proportion of the ith constituent in the mixture by x_i, then $x_i \geq 0$, $i = 1, 2, \dots, q$ and $\sum_{i=1}^{q} x_i = 1$. To find the experimental samples of distribution proportion, the methods of the ellipsoidal region and the largest sphere were used, and Equations (1) to (5) were established.

$$\text{Objective} \quad x_1 + x_2 + x_3 = 1 \tag{1}$$

Subject to

$$\left(\frac{x_1 - 0.45}{0.15}\right)^2 + \left(\frac{x_2 - 0.35}{0.15}\right)^2 + \left(\frac{x_3 - 0.35}{0.10}\right)^2 \leq 1 \tag{2}$$

$$0.30 \leq x_1 \leq 0.60 \tag{3}$$

$$0.20 \leq x_2 \leq 0.50 \tag{4}$$

$$0.25 \leq x_3 \leq 0.45 \tag{5}$$

x_1, x_2 and x_3 are the distribution proportion of the obtaining quantities for Hospital A, Hospital B and Hospital C, respectively.

Equations (1) to (5) establish the sample (x_1, x_2, x_3) as an infinite solution. Because the formulation from Equations (1) to (5) was a problem of nonlinear programming to find (x_1, x_2, x_3), GA was used here. One hundred samples were obtained. For example, (0.433327, 0.240389, 0.326284) were included in the 100 samples.

Step 3: Use an NN to establish the relationship between samples using the index of the HSCM's total system cost and patient safety.

The backpropagation (BP) of NNs was used to establish a black-box mathematical model among samples using the index of the HSCM's total system cost and patient safety. However, to establish the black-box model, training data and testing data among samples as well as the total cost and service level for each hospital should have been collected. Because this data was not available, this paper used a simulation method to produce the necessary data. The simulation method was applied to the responses of the 100 samples to each hospital's ranges of total cost and service level. The data was categorized as follows: Hospital A's total cost (TC_1) and service level ($S.L_1$); Hospital B's total cost (TC_2) and service level ($S.L_2$); and Hospital C's total cost (TC_3) and service level ($S.L_3$). As Table 1 illustrates, if the sample were (0.433327, 0.240389, 0.326284), TC_1 would be \$120,000-\$140,000 by simulation, $S.L_1$would be 0.85-0.90 by simulation; TC_2 would be \$14,000-\$18,000 by simulation, $S.L_2$ would be 0.80-0.90 by simulation; and TC_3 would be \$12,000-\$15,000 by simulation, $S.L_3$ would be 0.88-0.96 by simulation. Table 2 shows the maximum and minimum of each hospital's total cost and service level from the simulation result.

TABLE 1. Interval estimations for distribution proportion, total cost, and service level for each hospital

Hospital A		
Interval estimation of distribution proportion	Interval estimation of total cost	Interval estimation of service level
0.30-0.35	\$100,000-\$120,000	0.80-0.85
0.35-0.45	\$120,000-\$140,000	0.85-0.90
0.45-0.55	\$140,000-\$160,000	0.90-0.95
0.55-0.60	\$160,000-\$180,000	0.95-1.00
Hospital B		
Interval estimation of distribution proportion	Interval estimation of total cost	Interval estimation of service level
0.20-0.25	\$140,000-\$180,000	0.80-0.90
0.25-0.30	\$180,000-\$210,000	0.90-0.92
0.30-0.35	\$210,000-\$240,000	0.92-0.94
0.35-0.40	\$240,000-\$270,000	0.94-0.96
0.40-0.45	\$270,000-\$300,000	0.96-0.98
0.45-0.50	\$300,000-\$330,000	0.98-1.00
Hospital C		
Interval estimation of distribution proportion	Interval estimation of total cost	Interval estimation of service level
0.25-0.30	\$90,000-\$120,000	0.80-0.88
0.30-0.35	\$120,000-\$150,000	0.88-0.96
0.35-0.40	\$150,000-\$180,000	0.96-0.98
0.40-0.45	\$180,000-\$200,000	0.98-1.00

TABLE 2. The specifications for each hospital

Hospital	Total cost		Service level	
	maximization	minimization	maximization	minimization
A	156,973	121,207.1	0.93158	0.85092
B	209,642	140,089.7	0.91916	0.80142
C	149,953	92,746.2	0.95984	0.81011

In order to use these data as training data and test data in BP, after producing the simulation data this data was transferred to a 0-1 value. Because TC_1, TC_2 and TC_3 illustrate the principle of "the-smaller-the-best" and $S.L_1$, $S.L_2$ and $S.L_3$ illustrate the principle of "the-larger-the-best", total cost and service level are in conflict with one other. They have a trade-off effect. In this case, the desirability function is used to achieve the simultaneous goal. The desirability function, was used to transfer total cost to a 0-1 value, DTC_i (for $i = 1, 2, 3$), in Equation (6), and to transfer service level to a 0-1 value, $DS.L_i$ (for $i = 1, 2, 3$), in Equation (7) [35].

$$DTC_i = \begin{cases} 1, & TC_i \leq TC_i^{\min} \\ \left(\frac{TC_i - TC_i^{\max}}{TC_i^{\min} - TC_i^{\max}}\right), & TC_i^{\min} \leq TC_i \leq TC_i^{\max}, \\ 0, & TC_i \geq TC_i^{\max}, \end{cases} \tag{6}$$

where $TC_i^{\min}$ is the lowest value of TC_i and $TC_i^{\max}$ is the highest value of TC_i, $i = 1, 2, 3$.

$$DS.L_i = \begin{cases} 0, & S.L_i \leq S.L_i^{\min} \\ \left(\frac{S.L_i - S.L_i^{\min}}{S.L_i^{\max} - S.L_i^{\min}}\right), & S.L_i^{\min} \leq S.L_i \leq S.L_i^{\max}, \\ 1, & S.L_i \geq S.L_i^{\min} \end{cases} \tag{7}$$

where $S.L_i^{\min}$ is the lowest value of $S.L_i$ and $S.L_i^{\max}$ is the highest value of $S.L_i$, $i = 1, 2, 3$.

In order to integrate DTC_i (for $i = 1, 2, 3$) into an index performance of the HSCM's total system cost, the index performance was calculated as $DTC = \sqrt[3]{\prod DTC_i}$. Similarly, in order to integrate $DS.L_i$ (for $i = 1, 2, 3$) into an index performance of the HSCM's service level, the index performance was calculated as $DS.L = \sqrt[3]{\prod DS.L_i}$.

After obtaining the HSCM's index performance of total system cost and service level, the BP mathematical model was established. The BP consists of an input layer, a hidden layer, and an output layer. The network structure is depicted in Figure 1 with three input nodes and two output nodes. The data for input nodes are x_1, x_2 and x_3. The data for output nodes are DTC and $DS.L$. Ninety of the 100 samples were used for training data and 10 for testing data. The network parameter learning rate and moment was set to assist the trained network to attempt convergence and stabilization of the training behavior. The stopping criterion was set to lower the root mean square error (RMSE) in the training and testing processes. The result is shown in Table 3. The iteration was set to 10,000, the momentum rate was set to 0.08, and the learning rate was set to dynamically auto-adjust from 0.001 to 0.300 for rapid, effective learning and stable behavior (mildly varying values of RMSE). Table 3 lists several candidates of the network architecture. The architecture 3-8-2 (input nodes-hidden nodes-output nodes) BP mathematical model was selected because it had the lowest RMSE in the training and testing and therefore offered better performance.

Step 4: Use a GA to obtain the optimal distribution proportion for each hospital.

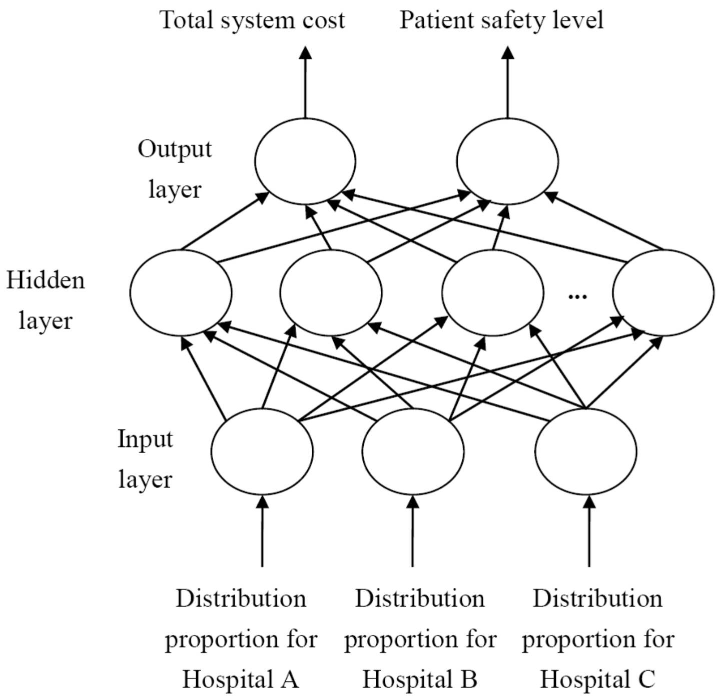

FIGURE 1. A BP mathematical model

Table 3. BP mode options for this study

BP model	RMSE	
	Training	Testing
3-5-2	0.02097	0.03020
3-6-2	0.02023	0.02935
3-7-2	0.02193	0.02852
3-8-2	**0.02046**	**0.02617**
3-9-2	0.02070	0.02838
3-10-2	0.02109	0.02854
3-11-2	0.02122	0.02904

BP model: input nodes-hidden nodes-output nodes
Leaning rate: 0.001∼0.300
Momentum rate: 0.08
Iteration: 10,000

In this step, the authors used a GA to search the 3-8-2 BP mathematical model to obtain the optimal distribution proportion for each hospital. In general, a GA produces an initial set of random solutions called a population (the population of guesses). Each individual in the population is a feasible solution to the problem and is called a chromosome. A chromosome is a string type organized by a sequence of the values (e.g., x_1, x_2, x_3) for the problem. For this paper, x_1, x_2 and x_3 were limited to a value between 0 and 1 and they were combined into one string (**N**, **O**, **P**) to represent chromosomal structure. Different numbers in the primary population were examined to select the most suitable population size through the limitation of $x_1 + x_2 + x_3 = 1$. Fifty strings were randomly generated to establish the initial population.

Chromosomes go through successive iterations called generations. When each generation is run, the fitness function is used to evaluate the chromosomes. To create the next generation, the GA applies a reproduction operator to select the candidate chromosomes based on the fitness function. In this paper, the two index performances – DTC and $DS.L$ – needed to be integrated into one overall performance, or fitness function, to be simultaneously optimized by a GA. The larger the fitness value, the higher the overall performance. The fitness function was represented as $\sqrt{DTC * DS.L}$.

The essential operators, including reproduction, crossover and mutation, needed to be determined in advance when the GA was applied to optimizing distribution proportion for each hospital. The roulette wheel approach was thus adopted as the selection procedure. The mutation rate was determined automatically. The crossover rate was set as 0.5. The mutation rate and the crossover rate controlled the expected number of chromosomes to mate and the number of genes to mutate, respectively [35,36].

A common method of terminating a GA is to test after a pre-specified number of generations the quality (convergence at the global optimum) of the best members of the population against the tested problem definition. The stopping condition of the GA procedure was set at 5,000 iterations or when the change in the previous 1,000 iterations was less than 1%. The optimal distribution proportion for (x_1^*, x_2^*, x_3^*) was determined to be (0.476, 0.273, 0.251). That is, Hospital A dispatched 23,800 tablets (50,000 tablets $*$ 0.476), Hospital B dispatched 13,650 tablets (50,000 tablets $*$ 0.273), and Hospital C dispatched 12,550 tablets (50,000 tablets $*$ 0.251). Also, the results show that Hospital A had a total cost of \$140,000-\$160,000 and a service level of 0.90-0.95. Hospital B had a total cost of \$180,000-\$210,000 and a service level of 0.90-0.92. Hospital C had a total cost of \$90,000-\$120,000 and a service level of 0.80-0.88. The HSCM's total system cost was between \$410,000 and \$490,000. The HSCM's service level was between 0.865 ($\sqrt[3]{0.90 * 0.90 * 0.80}$) and 0.916.

In this case, in the practical problem, to face the difficult information sharing of internal costs among the hospitals, the quantities dispatched to each hospital are always dependent on each hospital's demand. That is, Hospital A's distribution proportion in the practical problem can be derived, using the formulation:

$$\frac{\text{Hospital A's demand}}{\text{Hospital A's demand} + \text{ Hospital B's demand} + \text{ Hospital C's demand}}.$$

Also, the distribution proportion's formulations of Hospital B and Hospital C are the same as the formulation of Hospital A. For example, according to the hospitals' demands to compute the distribution proportion, if Hospital A's distribution proportion is 0.36, Hospital B will be 0.36, and Hospital C will be 0.28. According to Table 1, the total system cost will be between 450000 and 530000, which is higher than the total system cost between \$410,000 and \$490,000 when the optimal distribution proportion for Hospital A, Hospital B, and Hospital C is 0.476, 0.273, and 0.251. Simultaneously, the service level will be between 0.861 ($\sqrt[3]{0.85 * 0.94 * 0.80}$) and 0.913, which is lower than the service level between 0.865 ($\sqrt[3]{0.90 * 0.90 * 0.80}$) and 0.916 when the optimal distribution proportion for Hospital A, Hospital B, and Hospital C is 0.476, 0.273, and 0.251. Hence, the comparison results between the practical distribution proportion and the innovative distribution proportion approach show that in the innovative distribution proportion approach, the solutions for the total system cost and service level are superior to those in the practical distribution proportion.

4. **Sensitivity Analysis.** In order to obtain an adjustable strategy for the HSCM for dispatching medicine, the sensitivity analysis of distribution proportion was explored.

Based on the optimal distribution proportion for (0.476, 0.273, 0.251), if the authors were to fix the distribution proportion for Hospital A at 0.476, then Hospital B could decrease the distribution proportion by 0.05, that is from 0.273 to 0.223, (0.273→0.223), and Hospital C could increase the distribution proportion by 0.05 (0.251→0.301). The HSCM's total system cost would then be between \$400,000 and \$490,000. The HSCM's service level index would then be between 0.858 and 0.936. If the distribution proportion of Hospital A were fixed at 0.476, then Hospital B could increase the distribution proportion by 0.05 (0.273→0.323) and Hospital C could decrease the distribution proportion by 0.05 (0.251→0.201). However, in this situation, the decrease of the distribution proportion of 0.05 by Hospital C, (0.251→0.201) would not be possible because the lowest distribution proportion was fixed at 0.250.

If the distribution proportion for Hospital B were fixed at 0.273, then Hospital A could decrease the distribution proportion by 0.05 (0.476→0.426) and Hospital C could increase the distribution proportion by 0.05 (0.251→0.301). The HSCM's total system cost would then be between \$420,000 and \$500,000. The HSCM's service level index would be between 0.876 and 0.926. If the distribution proportion of Hospital B were fixed at 0.273, then Hospital A could increase the distribution proportion by 0.05 (0.476→0.526) and Hospital C could decrease the distribution proportion by 0.05 (0.251→0.201). However, in this situation, the decrease of the distribution proportion of 0.05 by Hospital C, (0.251→0.201) would not be possible because the lowest distribution proportion was fixed at 0.250.

If the distribution proportion for Hospital C were fixed at 0.251, then Hospital A could decrease the distribution proportion by 0.05 (0.476→0.426) and Hospital B could increase the distribution proportion by 0.05 (0.273→0.323). The HSCM's total system cost would then be between \$420,000 and \$500,000. The HSCM's service level index would be between

0.855 and 0.906. If the distribution proportion of Hospital C were fixed at 0.252, then Hospital A could increase the distribution proportion by 0.05 (0.476→0.526) and Hospital B could decrease the distribution proportion by 0.05 (0.273→0.223). The HSCM's total system cost would then be between \$370,000 and \$460,000. The HSCM's service level index would be between 0.832 and 0.910.

The results of sensitivity analysis show that using an adjustable strategy for the HSCM means that when Hospital A needs higher quantities, supply quantities must come from Hospital B. In addition, when Hospital B needs higher quantities, supply quantities must come from Hospital A. When Hospital C needs higher quantities, if Hospital A supplies them then the HSCM's total system cost would be higher than that if Hospital B supplied them. Also, if Hospital A supplies them then the HSCM's service level index would be between 0.0.876 and 0.926, and if Hospital B supplies them then the HSCM's service level index would be between 0.858 and 0.936.

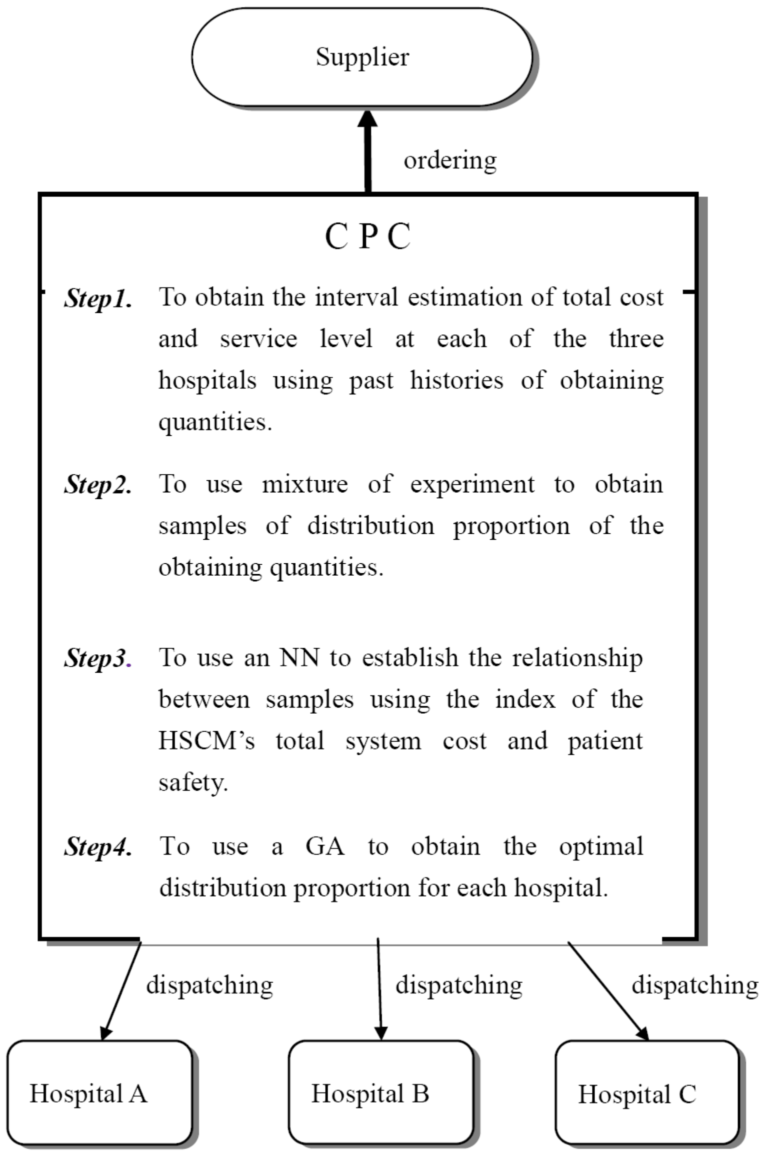

Figure 2. An innovative distribution proportion approach for medicines for hospitals that have combined their hospital supply chain management for the centralized purchasing of medicines

5. **Conclusion.** In this paper, the authors created an innovative distribution proportion approach to treat a distribution problem for centralized purchasing when the open information sharing of internal costs of each hospital is difficult. Figure 2 shows the four steps of the innovation distribution approach: obtaining each hospital's interval estimation of total cost and service level, obtaining samples of distribution proportion, establishing the relationship among samples with the index of HSCM's total system cost and service level, and obtaining the optimal distribution proportion for each hospital. In addition, to compare the practical distribution proportion with the innovative distribution proportion approach, the results show that in the innovative distribution proportion approach, the total system cost and service level are better than those in the practical distribution proportion method. It means that the innovative distribution proportion approach takes the whole hospitals' related cost and service levels into consideration to obtain the optimal distribution proportion, which is superior to the practical distribution proportion method, which only takes the demands of each hospital into consideration to compute the distribution proportion. That is, when decision makers are in consideration of the HSCM based on the total system cost and patient safety for the distribution problem, the concept of "supply chain" must be also taken into consideration even if the hospitals cannot share information of internal costs with each other.

Also, sensitivity analysis was used to obtain an adjustable strategy for dispatching quantities. The most important contribution of this paper is its presentation of an innovative distribution proportion approach to solve a practical problem: even when individual hospitals have no desire to share information related to internal costs, the hospitals can still quickly obtain dispatched quantities of medicines to each hospital. Overall, this paper presents a new research perspective in the field of supply chain management.

REFERENCES

[1] H. Zijm and J. Timmer, Coordination mechanisms for inventory control in three-echelon serial and distribution systems, *Annals of Operations Research*, vol.158, pp.161-182, 2008.

[2] R.-S. Chen and M. Tu, Development of an agent-based system for manufacturing control and coordination with ontology and RFID technology, *Expert Systems with Applications*, vol.36, pp.7581-7593, 2009.

[3] C.-L. Chu and V. J. Leon, Scalable methodology for supply chain inventory coordination with private information, *European Journal of Operational Research*, vol.195, pp.262-279, 2009.

[4] A. Pan, S. Y. S. Leung, K. L. Moon and K. W. Yeung, Optimal reorder decision-making in the agent-based apparel supply chain, *Expert Systems with Applications*, vol.36, pp.8571-8581, 2009.

[5] M. S. Sajadieh, M. R. A. Jokar and M. Modarres, Developing a coordinated vendor-buyer model in two-stage supply chains with stochastic lead-times, *Computers & Operations Research*, vol.36, pp.2484-2489, 2009.

[6] E. Fleisch and C. Tellkamp, Inventory inaccuracy and supply chain performance: A simulation study of a retail supply chain, *International Journal of Production Economics*, vol.95, pp.373-385, 2005.

[7] C. Zhang and C. Zhang, Design and simulation of demand information sharing in a supply chain, *Simulation Modelling Practice and Theory*, vol.15, pp.32-46, 2007.

[8] F. Longo and G. Mirabelli, An advanced supply chain management tool based on modeling and simulation, *Computers & Industrial Engineering*, vol.54, pp.570-588, 2008.

[9] Y.-J. Chen and Y.-M. Chen, An XML-based modular system analysis and design for supply chain simulation, *Robotics and Computer-Integrated Manufacturing*, vol.25, pp.289-302, 2009.

[10] D. Kofjac, M. Kljajic and V. Rejec, The anticipative concept in warehouse optimization using simulation in an uncertain environment, *European Journal of Operational Research*, vol.193, pp.660-669, 2009.

[11] T. Kitagawa, T. Maruta, Y. Ikkai and N. Komoda, A description language based in multi-functional modeling and a supply chain simulation too, *Proc. of IEEE International Conference on Systems, Man, and Cybernetics*, vol.3, pp.2287-2292, 2000.

[12] D. P. van Donk, Redesigning the supply of gasses in a hospital, *Journal of Purchasing and Supply Management*, vol.9, pp.225-233, 2003.

[13] L. Nicholson, A. J. Vakharia and S. S. Erenguc, Outsourcing inventory management decisions in healthcare: Models and application, *European Journal of Operational Research*, vol.154, pp.271-290, 2004.

[14] S. D. Lapierre and A. B. Ruiz, Scheduling logistic activities to improve hospital supply system, *Computers & Operations Research*, vol.34, pp.624-641, 2007.

[15] H.-C. Liao, Using GA to dispatch the obtaining quantity for minimizing the total cost based on consideration of patient safety in HSCM, *Expert Systems with Application*, vol.36, pp.11358-11362, 2009.

[16] H.-M. Tzeng, Crisis management policies and programs to prevent nursing-related medical disputes in Taiwanese hospitals, *Nursing Economics*, vol.23, no.5, pp.239-247, 2005.

[17] H.-M. Tzeng and C.-Y. Yin, The staff-working height and the designing-regulation height for patient beds as possible causes of patient falls, *Nursing Economics*, vol.24, no.6, pp.323-327, 2006.

[18] B. Widrow, D.-E. Rumelhart and M.-A. Lehr, Neural networks: Applications in industry, business and science, *Communications of the ACM*, vol.37, no.3, pp.93-105, 1994.

[19] J. D. Dillon and M. O'Malley, A Lagrangian augmented Hopfield network for mixed integer non-linear programming problems, *Neurocomputing*, vol.42, no.1-4, pp.323-330, 2002.

[20] N. S. Bhuvaneswari, G. Uma and T. R. Rangaswamy, Adaptive and optimal control of a non-linear process using intelligent controllers, *Applied Soft Computing*, vol.9, no.1, pp.182-190, 2009.

[21] U.-P. Wen, K.-M. Lan and H.-S. Shih, A review of Hopfield neural networks for solving mathematical programming problems, *European Journal of Operational Research*, vol.198, no.3, pp.675-687, 2009.

[22] D. E. Goldberg, *Genetic Algorithm in Search, Optimization and Machine Learning*, Addison-Wesley, New York, 1989.

[23] D. B. Fogel, An introduction to simulated evolutionary optimization, *IEEE Transactions on Neural Networks*, vol.5, no.1, pp.3-14, 1994.

[24] P. Kelle and A. Akbulut, The role ERP tools in supply chain information sharing, cooperation, and cost optimization, *International Journal of Production Economics*, vol.93/94, pp.41-52, 2005.

[25] B. K. Lee, K. H. Kang and Y. H. Lee, Decomposition heuristic to minimize total cost in a multi-level supply chain network, *Computers & Industrial Engineering*, vol.54, no.4, pp.945-959, 2008.

[26] R. Z. Farahani and M. Elahipanah, A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain, *International Journal of Production Economics*, vol.111, no.2, pp.229-243, 2008.

[27] S. R. Yadav, R. R. M. R. Muddada, M. K. Tiwari and R. Shankar, An algorithm portfolio based solution methodology to solve a supply chain optimization problem, *Expert Systems with Application*, vol.36, no.4, pp.8407-8420, 2009.

[28] M. A. Darwish, Economic selection of process mean for single-vendor single-buyer supply chain, *European Journal of Operational Research*, vol.199, no.1, pp.162-169, 2009.

[29] R. E. Spekman, J. W. Kmamuff and N. Myhr, An empirical investigation into supply chain management: A perspective on partnerships, *International Journal of Physical Distribution & Logistics Management*, vol.28, no.8, pp.630-650, 1998.

[30] C. E. Schmidt, Improving medication safety and patient care in the emergency department, *Journal of Emergency Nursing*, vol.29, no.1, pp.12-16, 2003.

[31] J. B. Dimick, J. D. Birkmeyer and G. R. Upchurch, Measuring surgical quality: What's the role of provider volume? *World Journal of Surgery*, vol.29, pp.1217-1221, 2005.

[32] N. Menachemi and R. G. Brooks, Reviewing the benefits and costs of electronic health records and associated patient safety technologies, *Journal of Medical Systems*, vol.30, pp.159-168, 2006.

[33] A. Rogers, E. Jones and D. Oleynikov, Radio frequency identification (RFID) applied to surgical sponges, *Surgical Endoscopy*, vol.21, pp.1235-1237, 2007.

[34] J. A. Cornell, *Experiments with Mixtures*, John Wiley & Sons, Inc., 1990.

[35] G. Derringer and R. Suich, Simultaneous optimization of several response variables, *Journal of Quality Technology*, vol.12, no.4, pp.214-218, 1980.

[36] M. Gen and R. Cheng, *Genetic Algorithms and Engineering Design*, John Wiley & Sons, 1997.